Indian J. Phys. 79 (5), 473-483 (2005)

AN INTERNATIONAL JOURNAL
IJP

Neuro-fuzzy modelling of the strength of thermomechanically processed HSLA steels

S Datta* and M K Banerjee
Department of Metallurgy & Materials Engineering, B E S. University, Shibpur, Howrah-711 103, West Bengal, India

E-mail sdatta@matsc.becs.ac in

Received 21 September, 2004, accepted 16 March, 2005

Abstract : The mechanical properties of HSLA steels are modelled by the application of neuro-fuzzy systems in respect of the effect of composition and process parameters. Neuro-fuzzy system generated through data clustering showed a good performance from the prediction point of view. Also the increase in the number of rules improved the predictability of the system. A new design of neuro-fuzzy system through division in sub-classes has enabled the system to model a complicated system of non-linear input-output relationship.

Keywords . HSLA steel, mechanical property, neuro-fuzzy system, prediction

PACS Nos. 81 05 Bx, 84 35 +i, 07 05 Mh

1. Introduction

The mechanical properties of steels are known to depend on independent variables like composition and process parameters. Efforts to develop a model relating the independent variables with the dependent ones are still continuing. The main reason for the lack of progress in perfect prediction of mechanical properties as a function of composition and process parameters is that a particular property, say, yield strength (YS) is dependent in a very complex way on a number of variables. Nevertheless, there ought to exist some specific hidden patterns, which relate the inputs with the outputs. So far, these have been recognised only qualitatively by the experts in materials science. In order to make a quantitative assessment of the effect of composition/process variables in steel onto its ultimate properties, it is necessary to envisage a black box, capable of developing a relationship between the variables.

Artificial neural network (ANN), differential equations, multidimensional analyses can act as such black boxes, which enable the accurate mapping of inputs to an appropriate, output space. Several efforts have been made to model the mechanical properties of high strength low alloy (HSLA) steel using neural network [1-5]. Even fuzzy logic can make up a black box. This is particularly useful as fuzzy logic is conceptually easier to understand. Fuzzy logic is capable of modelling non-linear arbitrary relationships and is highly tolerant of imprecise data. Since fuzzy logic can be built with the help of the experience of expert, the system remains highly compatible with the real life situation [6-9]. However the prediction process can be made much more precise by using neuro-fuzzy system, which incorporates adaptive technique to develop the final relationship between the inputs and the output variable. Fuzzy inference systems (FIS) use the experts' knowledge for prediction, whereas adaptive neuro-fuzzy inference systems (ANFIS) possess the capacity to utilise the prior knowledge of the expert and to further refine the results of FIS through the artificial learning process. Thus, the lack of transparency in ANN modelling, which does not take into account the expert knowledge, can be avoided. Application of neuro-fuzzy systems in case of fatigue of Ni-based superalloys [10] and structure-property correlation in Al-Zn-Mg alloys [11] are documented in recent literatures. Efforts have been made by the present authors to apply fuzzy system in assessing the effects of compositional variables and the thermomechanical control processing (TMCP) parameters on the mechanical properties of steel. It has been demonstrated that the phenomena can be described in fuzzy inference systems through some if-then rules [12]. Observations have suggested

*Corresponding Author

that a high degree of precision in predicting the strength of steels may not be possible without further improvement in FIS. ANFIS is capable of taking care of this gap in FIS modelling through adaptive learning. As it is very useful to assess the uncertainty in the quantitative determination of strength properties of HSLA steels as a function of its chemical composition and TMCP parameters, attempts have been made to study the effect of composition and process parameters on the mechanical properties of HSLA steels by the application of neuro-fuzzy systems.

2. Database

The compositional variables *viz.* carbon (C), manganese (Mn), silicon (Si), nickel (Ni), copper (Cu), molybdenum (Mo), niobium (Nb), chromium (Cr), titanium (Ti) and boron (B), the process variables like slab reheating temperature (SRT), percentage deformation in different temperature zones (designated as D1, D2 and D3), finish rolling temperature (FRT) and cooling rate (CR) are used as input variables and yield strength (0.2% proof stress) is used as the output variable. The alloys used for the present work have been prepared in the laboratory and then control rolled in a laboratory scale two high rolling mills with 10 HP motor. The mechanical properties have been measured in INSTRON 4204. Similar data from published literatures have also been included to develop a database with wide variations. The range of variables used in the HSLA steel data is described in Table 1.

Table 1. The minimum and maximum limits of the parameters

Parameters	Minimum	Maximum
C	0	0.1
Mn	0	2
Si	0	0 5
Ni	0	4
Cu	0	2
Mo	0	2
Nb	0	0.1
Cr	0	1
Ti	0	0 05
B	0	0 003
SRT	1000	1250
D1	0	30
D2	10	40
D3	10	50
FRT	650	850
CR	0	35
UTS	600	1200
YS	300	1100
% el	10	25

3. Modelling technique

Fuzzy inference system enables mapping from a set of inputs to an output space by means of fuzzy logic. The FIS involves (a) membership function, (b) fuzzy logic operator and (c) if-then rule. A membership function (MF) is a curve that describes the mapping of each point in the input space to a membership value between 0 and 1, called the degree of membership (μ). There are quite a few types of membership functions, *viz.* triangular, trapezoidal, Gaussian, sigmoidal, asymmetrical polynomial *etc.* of which the Gaussian function is the most commonly used function and has been used in the present work. There are several types of fuzzy logic operator, of which the Sugeno-type [13] is used here. If-then rule statements are used to formulate the conditional statements between the inputs and the outputs. The if-then rule assumes the form.

If x is A then y is B,

where A and B are linguistic values defined by the fuzzy sets on the specific arrays. In our system, we can say if carbon is low then strength is low, (say).

On the other hand, the concept of artificial neural network used in the present case for adaptive learning of the FIS happens to be a supervised feed forward network trained with standard gradient descent backpropagation algorithms along with the least squares type of method. In the process of learning the error of the calculated or predicted output in relation to the actual output is backpropagated to adjust all the weight and bias values. A neuro-fuzzy inference system maps the inputs to an output space in a similar way. It comprises of membership function, fuzzy logic operator and if-then rules. The basic concept is to provide a method for the fuzzy modelling procedure to learn information about a data set in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. Ultimately, it constructs a FIS whose membership function parameters are adjusted using certain learning algorithm. This allows the fuzzy systems to learn from the data they are modelling. A network-type structure resembling that of a neural network then maps the inputs through their membership functions and associated parameters, and finally, the membership functions and associated parameters of the output is used to interpret the input/output relations. The parameters associated with the membership functions will change through the learning process. The modelling approach used by ANFIS is similar to any of the system identification techniques. The primary job is to hypothesise a parameterised model structure (relating inputs to membership functions to rules to outputs to membership functions), then to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion. This type of modelling yields best results if the training data presented to the ANFIS for training membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. So, if a large amount of data is collected, it will contain all the necessary representative features. There are certain other constraints in using ANFIS, *e.g.* it only supports Sugeno-type systems, and that is also with a single output, which is obtained by using the weighted average defuzzification (linear or constant output membership functions). Moreover, it cannot accept all the customisation options that basic fuzzy inference allows. That is, own membership functions and defuzzification functions cannot be used in this system.

The above concept is used for developing two systems, where composition and process parameters are used as inputs and yield strength is used as output. The database is used to train the Sugeno type FIS developed on the basis of some if-then rules relating the composition and process parameters with the yield strength of thermomechanically controlled processed HSLA steel. Besides training the FIS with a dataset through a learning algorithm, all the data were subjected to an operation called the clustering of numerical data. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of the system's behaviour. The cluster information can be used to generate a Sugeno-type fuzzy inference system to model the data behaviour using a minimum number of rules. The rules partition themselves according to the fuzzy qualities associated with each of the data clusters [14]. A comparative study between the predictions of the FIS itself, prediction of the FIS after neuro-adaptive learning and the learning of the generated FIS through data clustering is done.

4. The Neuro-fuzzy models

4.1 Relation of some alloy additions with yield strength (ANFIS-1):

Here the role of some alloy additions *viz.* niobium, titanium, copper and boron, in the enhancement of yield strength of HSLA steel have been modelled with the help of prior knowledge of physical metallurgy.

It has been found by earlier workers that boron, as a single addition, has no appreciable effect on the strength of HSLA steels. Although it increases the bainitic fraction, it increases the a grain size at the same time [15]. If boron is added in combination with niobium, a remarkable improvement in strength can be achieved. It is also reported that the presence of niobium and boron in combination retards the recrystallization of grains during TMCP [16]. Niobium and boron exerts a synergistic effect on the non- recrystallization temperature of austenite and increases it by about 25°C. This is ascribed to the non-equilibrium segregation of boron at dislocations and to the formation Nb-B complexes [17]. Addition of Ti with B has almost identical effect, although the grain refinement is relatively less significant than Nb-B steel [18]. Though the strengthening mechanism of copper is different from that of niobium or titanium, it also exhibits synergism with boron in a thermomechanically processed HSLA steel, as the precipitation of copper is delayed in boron treated steels. So microalloying of niobium and/or titanium in boron treated copper bearing HSLA steel has manifold effects on the strength property of steel [19-22]. This understanding has been used to develop a model of the relationship of these microalloying elements with the yield strength of the steel.

Regarding the data, niobium, titanium, copper and boron is taken within the range as stated in Table 1. Rest of the composition of the steel is 0.06 wt% C, 1.38 wt% Mn, 0.30 wt% Si, 1.12 wt% Ni, 0.55 wt% Mo and 0.78 wt% Cr. The fixed process parameters in all cases are slab reheating temperature (SRT) 1150°C, deformation in the recrystallisation temperature range (D1) 30%, in the non recrystallised temperature region (D2), 20% and in the ($\alpha + \gamma$) two phase region (D3), 25%. The finish rolling temperature (FRT) is taken as 750°C and cooling rate is 30°C/s. The resultant yield strength (YS) of the steel has varied between 800 to 1100 MPa. Primarily the process of auto generation of FIS through data clustering was done to achieve minimum error level. The output values were clustered to five groups, *viz.* low, low-medium, medium-medium, high-medium and high. Similarly all the inputs are also clustered into five groups (Figure 1). When the ANFIS is trained with linear output membership function (a feature of Sugeno type FIS) the inference

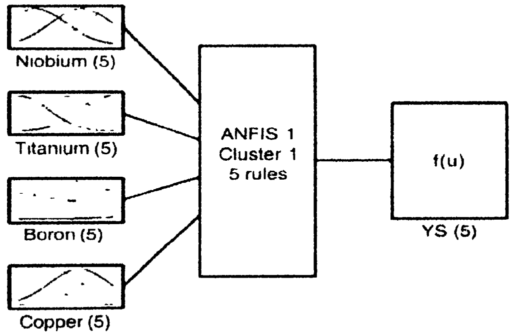

Figure 1. Structure of the ANFIS 1 generated by data clustering technique with five rules.

system is found to result into mergerance of a few input members together thereby leading to a less number of memberships. Thus, it may be noted that the membership functions of niobium, titanium and boron can be virtually treated as three membership functions, *viz.* low, medium and high after the training of the ANFIS is over whereas in case of copper it is four, *viz.* low, low-medium, high-medium and high. The five rules developed by the FIS are :

(i) if Nb is low and Ti is low and B is low and Cu is low then YS is low,

(ii) if Nb is low and Ti is medium and B is medium and Cu is low-medium then YS is low-medium,

(iii) if Nb is low and Ti is medium and B is medium and Cu is high-medium then YS is medium-medium,

(iv) if Nb is medium and Ti is medium and B is high and Cu is high then YS is high-medium,

(v) if Nb is high and Ti is high and B is high and Cu is high then YS is high.

The average error value of the ANFIS after training is found to be 12.5 MPa (Figure 2), which is more or less acceptable.

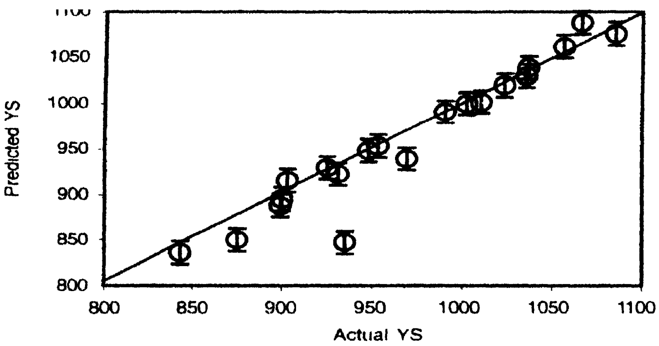

Figure 2. Actual *versus* predicted yield strength of ANFIS I generated through data clustering with five rules (after training).

In another exercise, an inference system is auto-generated with all the inputs and the output values clustered to seven groups, *viz.* very-low, low, low-medium, medium-medium, high-medium, high and very-high. Here also, FIS is found to have merged some of the membership functions of the inputs after training and each of niobium, copper and boron has been divided into four membership functions (against the seven taken initially) *viz.* low, low-medium, high-medium and high, membership functions; whereas in the case of titanium the total number of membership functions is five (low, low-medium, medium-medium, high-medium and high). The seven rules is seen to have reduced to five after the training of the ANFIS and these are:

(i) if Nb is low and Ti is low and B is low and Cu is low then YS is very-low,

(ii) if Nb is low and Ti is low-medium and B is low-medium and Cu is low-medium then YS is low,

(iii) if Nb is low and Ti is medium-medium and B is high-medium and Cu is high-medium then YS is low-medium,

(iv) if Nb is low-medium and Ti is medium-medium and B is high and Cu is high-medium then YS is medium-medium,

(v) if Nb is low-medium and Ti is medium-medium and B is high and Cu is high then YS is high-medium,

(vi) if Nb is high-medium and Ti is high-medium and B is high and Cu is high then YS is high,

(vii) if Nb is high and Ti is high and B is high and Cu is high then YS is very-high.

The average error value is further reduced to 10.3 MPa (Figure 3). It is noted from the above two cases that increasing the number of clusters and rules leads to a reduction in the error level. But further increase in clusters or rules will reduce the

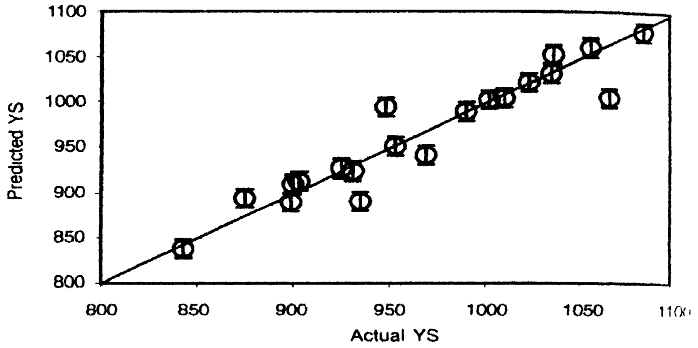

Figure 3. Actual *versus* predicted yield strength of ANFIS I generated through data clustering with seven rules after training

advantage of fuzzy systems, whose beauty lies in describing a system through simple linguistic expressions. So, taking clue from the above auto-generated FIS, it is decided to stick to the system of seven membership functions for the output and four for the inputs. The complicated rules generated by FIS through data clustering are made to look a bit simplified so that, with the understanding of the physical metallurgy of such steels, one can easily prepare the rules. The rules are as follows:

(i) if Nb is low and Ti is low and B is low and Cu is low then YS is very-low,

(ii) if Nb is low and Ti is low and B is low-medium and Cu is low-medium then YS is low,

(iii) if Nb is low-medium and Ti is low-medium and B is low-medium and Cu is low-medium then YS is low-medium,

(iv) if Nb is low-medium and Ti is low-medium and B is high-medium and Cu is high-medium then YS is medium-medium,

(v) if Nb is high-medium and Ti is high-medium and B is high-medium and Cu is high-medium then YS is high-medium,

(vi) if Nb is high-medium and Ti is high-medium and B is high and Cu is high then YS is high,

(vii) if Nb is high and Ti is high and B is high and Cu is high then YS is very-high.

Figure 4 shows the surface views depicting the relation deduced by the fuzzy system. When the system is used to plot the predicted versus actual output values before learning, depending only on the rule base, it was found to show a huge prediction error (average testing error 54.2 MPa) (Figure 5). After learning through hybrid algorithm the error value reduces to 13.9 MPa (Figure 6), which is reasonable for all practical purposes for an output range of 800 to 1100 MPa.

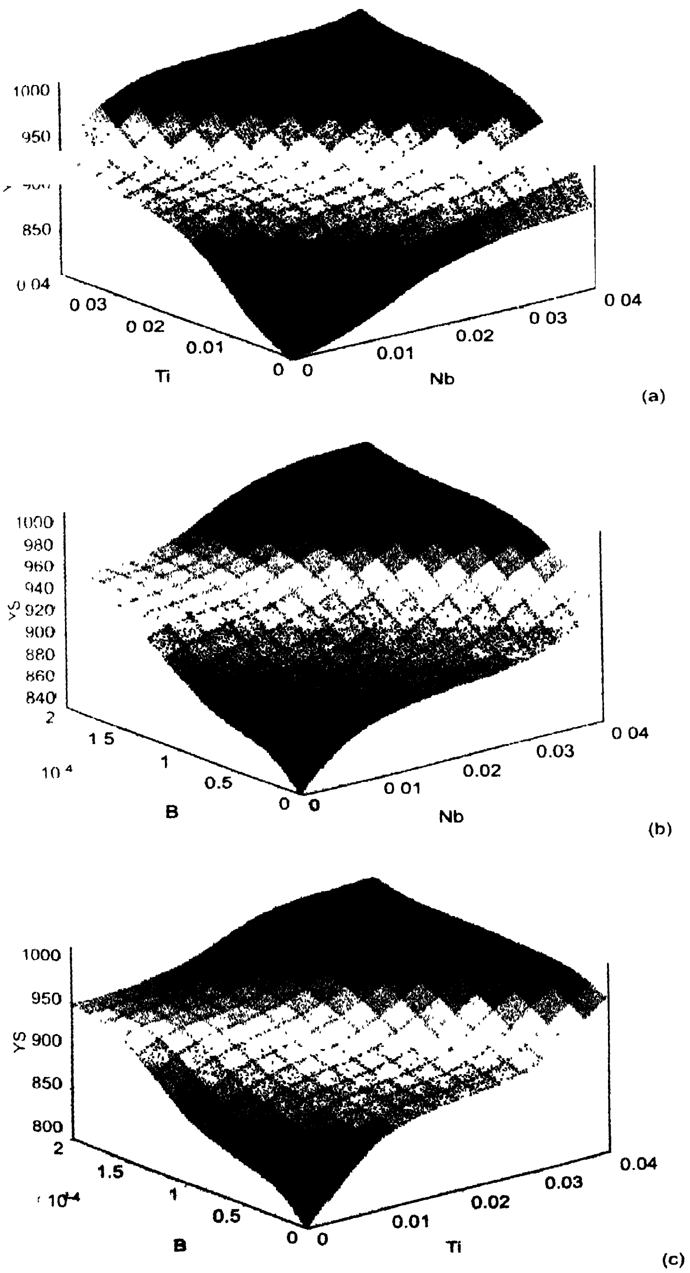

Figure 4. Surface view of the relations between yield strength and (a) Nb-Ti, (b) Nb-B and (c) Ti-B.

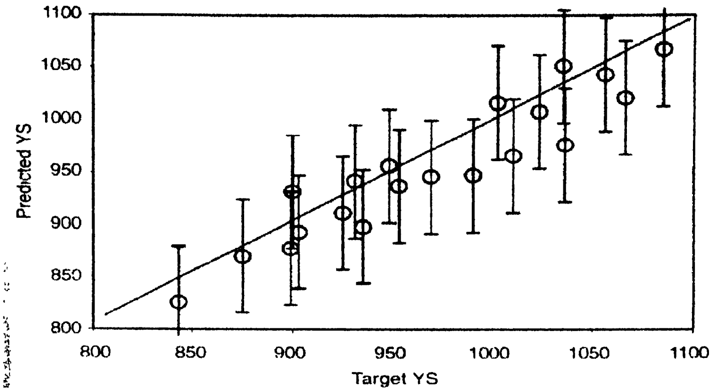

Figure 5. Actual *versus* predicted yield strength of ANFIS I with seven rules, generated on the basis of metallurgical understanding, (before training)

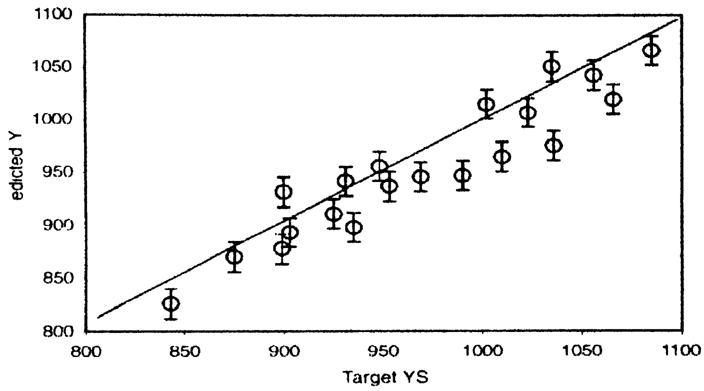

Figure 6. Actual *versus* predicted yield strength of ANFIS I with seven rules (after training)

4.2. Relationship of composition and process parameters with yield strength (ANFIS-II):

The relationships between the composition and process parameters with the strength are quite complicated. The available data have ten compositional and six process parameters to model the strength of thermomechanically processed HSLA steel. But it is difficult and in some way impractical to develop a single neuro-fuzzy system relating all these variables. The number of rules that will be required to define such a system will be enormously high to make the ANFIS predict reasonable results. So, all the inputs and their relations with the strength were divided into four subsystems, the outputs of those subsystems were then compounded into a final ANFIS to give the final strength of the steel (Figure 7).

4.2.1. Contribution of carbon, manganese, silicon, nickel and chromium (ANFIS IIA):

Carbon, manganese, silicon, nickel and chromium are the five elements most commonly present in steels. Carbon increases the tensile strength considerably by increasing the amount of pearlite in air-cooled steels, but it does so at the expense of weldability, cold formability and toughness. In hot rolled air cooled steel carbon exerts a negligible effect on the yield strength

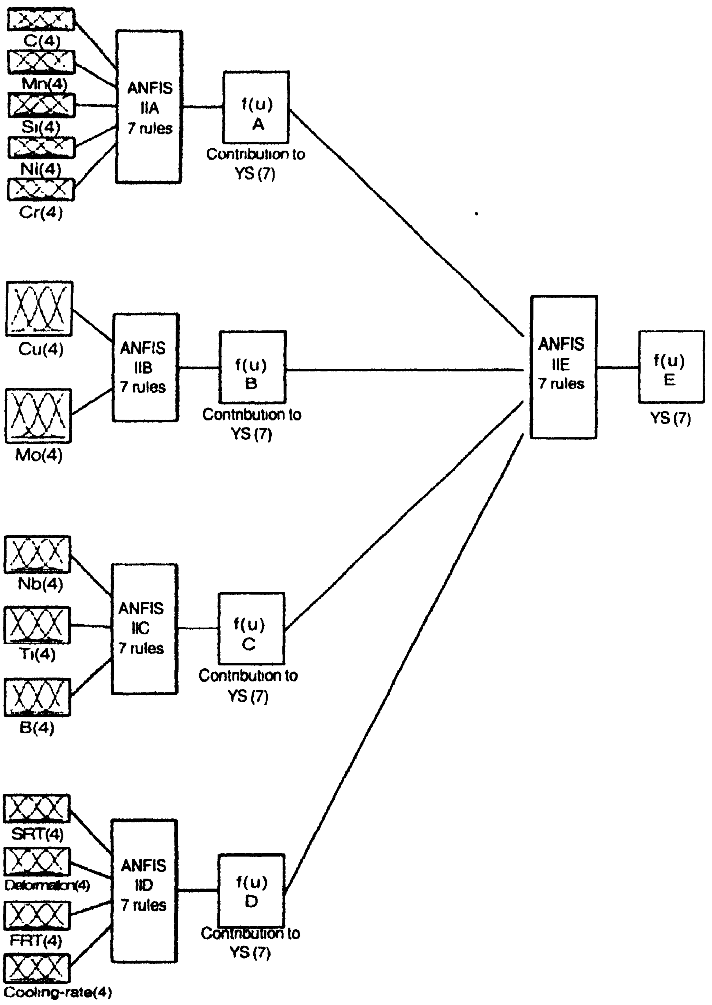

Figure 7. The structure of the ANFIS II.

[23]. The primary beneficial effect of manganese is its affinity for sulphur, which prevents the formation of the detrimental intergranular iron sulphides. In addition to this, manganese causes solid solution hardening. As a consequence of its austenite stabilizing effect, manganese depresses the $\gamma \rightarrow \alpha$ transformation temperature, and thus refines the α-grain, especially on rolling with large amounts of deformation in the lower temperature range. High addition of manganese increases yield strength markedly due to transformation hardening [24]. On the other hand, nickel and chromium enhances the strength of HSLA steel through solid solution hardening but also aids in precipitation of niobium carbides.

So from the available data, the contribution of each of these elements to the strength property has been calculated and is normalised within a range of 0 to1. The yield strength of the steel due to the minimum and maximum addition of each of the above elements, with other elements and process parameters remaining constant, are designated as x_{min} and x_{max} for that element. Then any value of yield strength, say x, for specific value of any the above elements is represented as the normalised contribution of that element to the yield strength, x_N, by the relation,

$$x_N = \frac{x - x_{min}}{x_{max} - x_{min}}. \quad (1)$$

As in the preceding case, the inputs are again divided into four membership functions and the output is divided into seven members. The seven rules designed to explain the system is stated below :

(i) if C is low and Mn is low and Si is low and Ni is low and Cr is low then YS is very-low,

(ii) if C is low and Mn is low and Si is low-medium and Ni is low-medium and Cr is low-medium then YS is low,

(iii) if C is low-medium and Mn is low-medium and Si is low-medium and Ni is low-medium and Cr is low-medium then YS is low-medium,

(iv) if C is low-medium and Mn is low-medium and Si is high-medium and Ni is high-medium and Cr is high-medium then YS is medium-medium,

(v) if C is high-medium and Mn is high-medium and Si is high-medium and Ni is high-medium and Cr is high medium then YS is high-medium,

(vi) if C is high-medium and Mn is high-medium and Si is high and Ni is high and Cr is high then YS is high,

(vii) if C is high and Mn is high and Si is high and Ni is high and Cr is high then YS is very-high

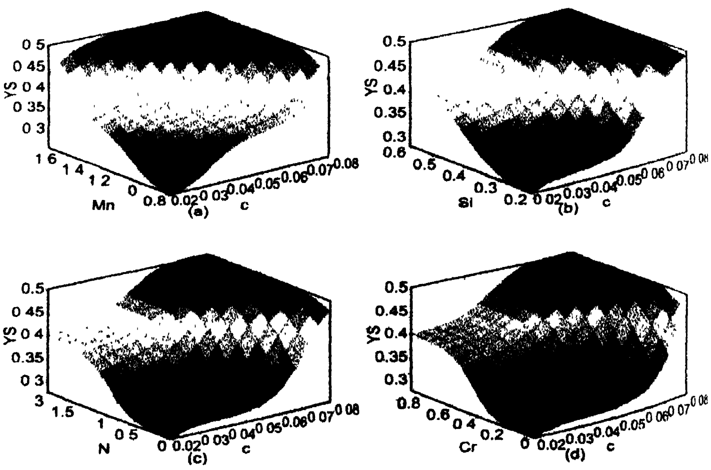

Figure 8. Surface view of the relations between yield strength and (a) C-Mn, (b) C-Si, (c) C-Ni and (d) C-Cr.

The relations between the strength and the concentration of the five elements are shown through surface plots (Figure 8). Before training, the data show an average error equal to 0.142 was obtained. After training the ANFIS, the error is finally reduced to 0.005 (Figure 9).

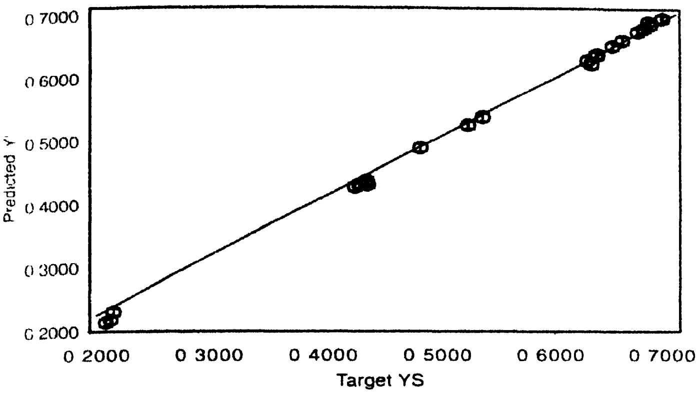

Figure 9. Actual *versus* predicted contribution to yield strength of ANFIS IIA after training.

4.2.2. Contribution of copper and molybdenum (ANFIS IIB) :

Among the substitutional alloying elements, copper and molybdenum is most common and both have significant effects on the yield strength of HSLA steel. Other than solid solution strengthening, copper is known to produce precipitation hardening when added in higher amount. From the available data, the contributions of these two elements have been separated and are normalized within a range of 0 to 1. The inputs are divided into four membership functions and the output is divided into seven members. The seven rules designed to explain the system is stated below :

(i) if Cu is low and Mo is low then YS is very low,

(ii) if Cu is low and Mo is low-medium then YS is low,

(iii) if Cu is low-medium and Mo is low-medium then YS is low-medium,

(iv) if Cu is low-medium and Mo is high-medium then YS is medium-medium,

(v) if Cu is high-medium and Mo is high-medium then YS is high-medium,

(vi) if Cu is high-medium and Mo is high then YS is high,

(vii) if Cu is high and Mo is high then YS is very high.

The surface view in Figure 10 shows the relation between copper, molybdenum and Yield strength. Here, the data show an average error equal to 0.119 before training. The trained ANFIS has predicted output with average error of 0.008 (Figure 11).

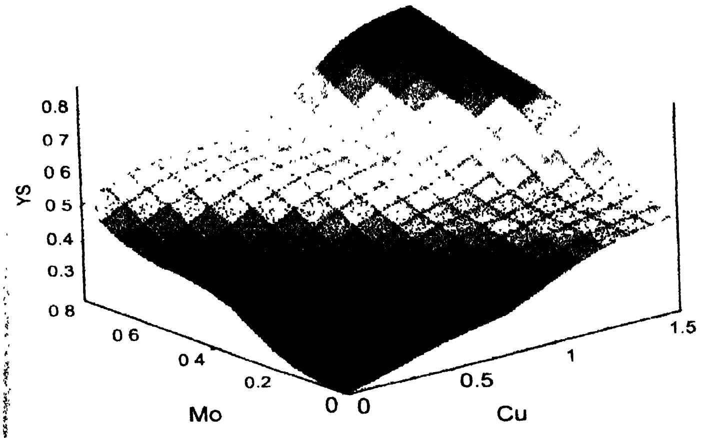

Figure 10. Surface view of the relations between copper, molybdenum and yield strength

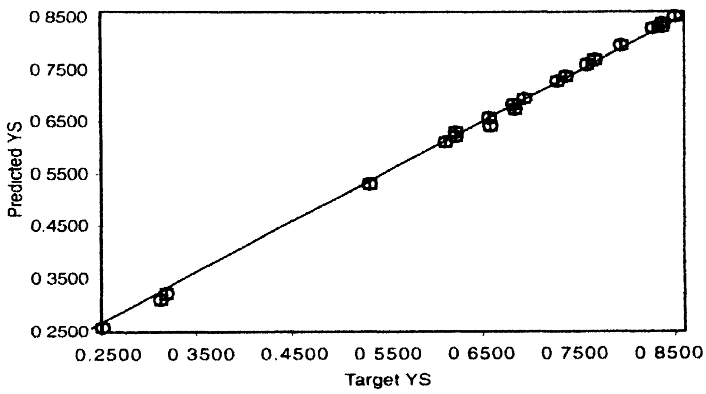

Figure 11. Actual *versus* predicted contribution to yield strength by ANFIS IIB (after training)

4.2.3. Contribution of niobium, titanium and boron (ANFIS IIC) :

Niobium, titanium and boron are the most important micro-alloying elements in HSLA steel due to their ability to strengthen steel through grain refinement as well as precipitation hardening. Similar to the earlier case, the inputs are divided into four membership functions and the normalised output is divided into seven members. The seven rules designed to explain the system is stated below:

(i) if Nb is low and Ti is low and B is low then YS is very low,

(ii) if Nb is low and Ti is low-medium and B is low-medium then YS is low,

(iii) if Nb is low-medium and Ti is low-medium and B is low-medium then YS is low-medium,

(iv) if Nb is low-medium and Ti is high-medium and B is high-medium then YS is medium-medium,

(v) if Nb is high-medium and Ti is high-medium and B is high-medium then YS is high-medium,

(vi) if Nb is high and Ti is high-medium and B is high then YS is high,

(vii) if Nb is high and Ti is high and B is high then YS is very high.

Before training, the data show an average error equal to 0.142, when the ANFIS is trained, the error is reduced to 0.022 (Figure 12).

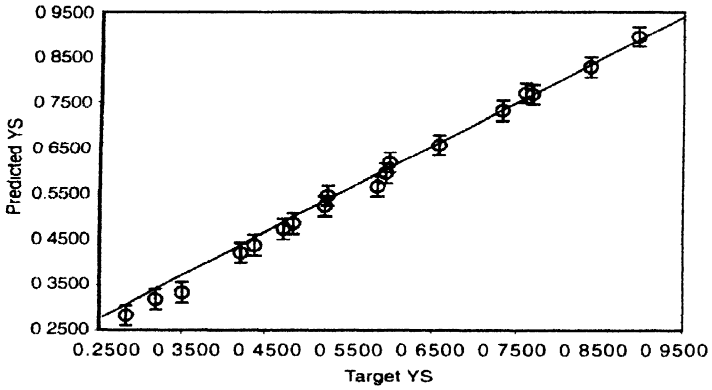

Figure 12. Actual *versus* predicted contribution to yield strength by ANFIS IIC (after training).

4.2.4. *Contribution of process parameters (ANFIS IID) :*

The process parameters *viz.* slab reheating temperature (SRT), percentage deformation (D), finish rolling temperature (FRT) and cooling rate (CR) are related to strength through the rules

(i) if SRT is high and D is low and FRT is high and CR is low then YS is very low,

(ii) if SRT is high-medium and D is low-medium and FRT is high and CR is low then YS is low,

(iii) if SRT is high-medium and D is low-medium and FRT is high-medium and CR is low-medium then YS is low-medium,

(iv) if SRT is low-medium and D is high-medium and FRT is high-medium and CR is low-medium then YS is medium-medium,

(v) if SRT is low-medium and D is high-medium and FRT is low-medium and CR is high-medium then YS is high-medium,

(vi) if SRT is low and D is high and FRT is low-medium and CR is high-medium then YS is high,

(vii) if SRT is low and D is high and FRT is low and CR is high then YS is very high.

Relation between the process parameters and yield strength is shown in Figure 13. Before training the ANFIS predicted an average error equal to 0.089. When the ANFIS is trained, the error is reduced to 0.018 (Figure 14).

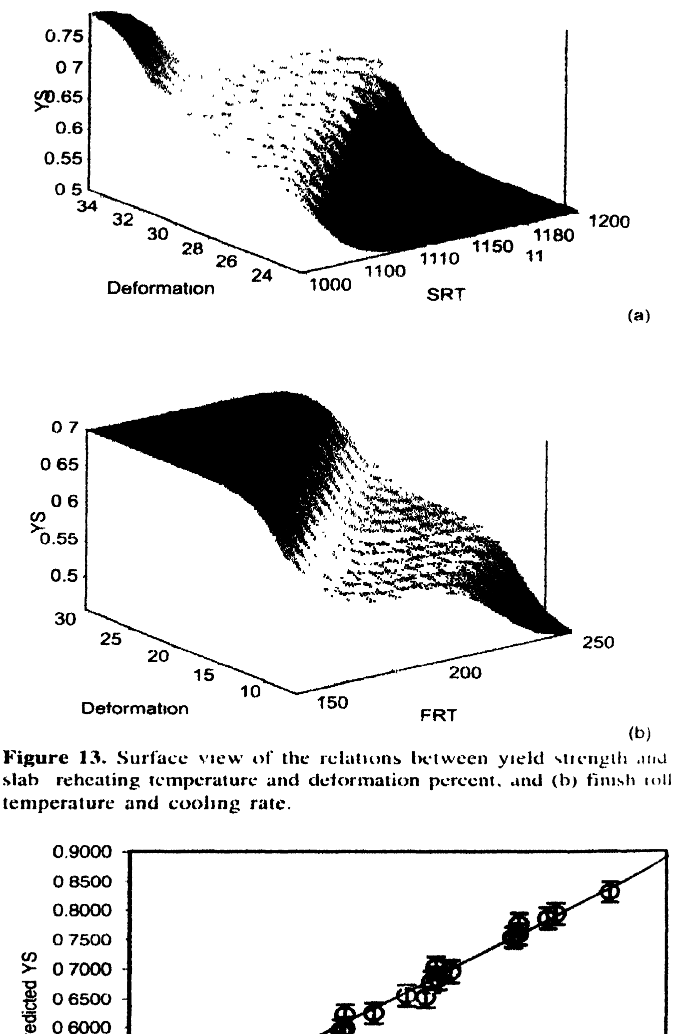

Figure 13. Surface view of the relations between yield strength and (a) slab reheating temperature and deformation percent, and (b) finish rolling temperature and cooling rate.

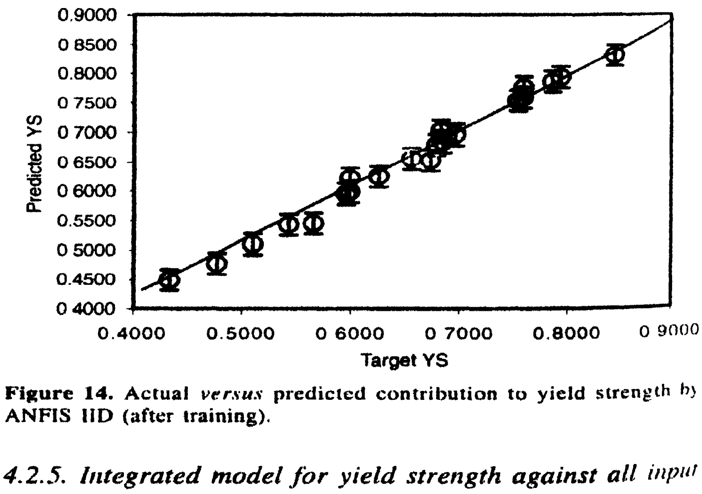

Figure 14. Actual *versus* predicted contribution to yield strength by ANFIS IID (after training).

4.2.5. *Integrated model for yield strength against all input variables (ANFIS IIE) :*

In the above four neuro-fuzzy models (ANFIS IIA to IID), the outputs may be considered as the contribution of elements (in the first three ANFISs) and process parameters (in the fourth ANFIS) towards the overall yield strength of the steel. It is seen that the outputs of these four systems have individually described the contributions of carbon-manganese-silicon-nickel-chromium (C *etc*), copper-molybdenum (Cu-Mo), niobium-titanium-boron (Nb-Ti-B) and the contribution of process parameters (proc.param.) towards the final yield strength value. These outputs (*i.e.*, the output of subsystems) are then integrated in ANFIS IIE to find out the final yield strength of the experimental steels. Therefore, these outputs of the subsystems constitute the inputs of ANFIS IIE, which assigns four memberships to each input. However, the output is divided into seven members. The rules formulated are as follows :

(i) if C *etc* is low and Cu-Mo is low and Nb-Ti-B is low and process parameters is low then YS is very low,

(ii) if C *etc* is low-medium and Cu-Mo is low-medium and Nb-Ti-B is low and proc.param. is low then YS is low,

(iii) if C *etc* is low-medium and Cu-Mo is low-medium and Nb-Ti-B is low-medium and proc.param. is low-medium then YS is low-medium,

(iv) if C *etc* is high-medium and Cu-Mo is high-medium and Nb-Ti-B is low-medium and proc.param. is low-medium then YS is medium-medium,

(v) if C *etc* is high-medium and Cu-Mo is high-medium and Nb-Ti-B is high-medium and proc.param. is high-medium then YS is high-medium,

(vi) if C *etc* is high and Cu-Mo is high and Nb-Ti-B is high-medium and proc.param. is high-medium then YS is high,

(vii) if C *etc* is high and Cu-Mo is high and Nb-Ti-B is high and proc.param. is high then YS is very high.

The ANFIS IIE predicted an average error equal to 58.51 MPa before training (Figure 15). The trained ANFIS prediction

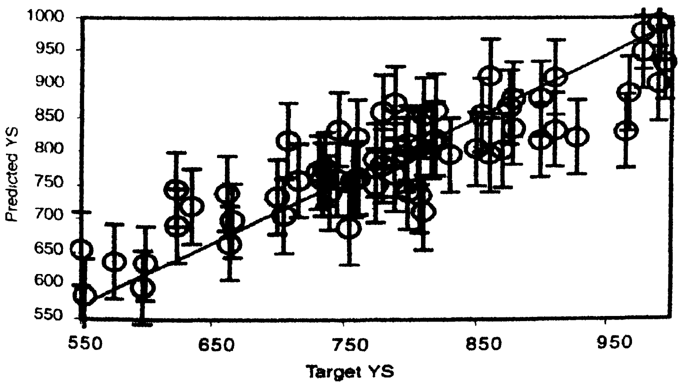

Figure 15. Actual *versus* predicted yield strength by ANFIS IIE (before training).

has shown a reduced error level of 12.5 MPa (Figure 16), which is quite acceptable for all practical purposes.

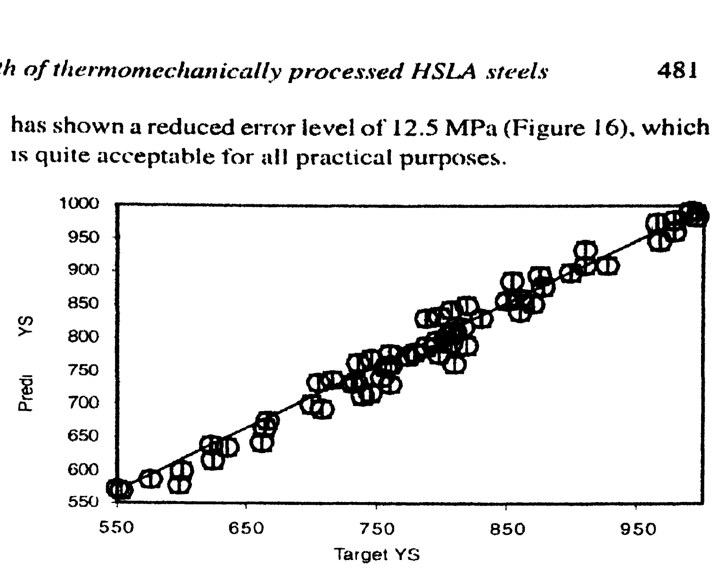

Figure 16. Actual *versus* predicted yield strength by ANFIS IIE after training

5. Discussion

When the process of learning is applied to the auto-generated neuro-fuzzy system, it has shown a good performance from the prediction point of view (Figures 2 and 3). Both the figures have shown a good match between the predicted and the target values. Moreover the error level in the range of 10-12 MPa for steels of above 800 MPa yield strength is considered to be acceptable for all practical purposes. This particular way of designing a fuzzy system through data clustering can be useful to gather knowledge about the relationships between the inputs and the outputs from some raw data where prior knowledge is nonexistent. Generation of neuro-fuzzy system through data clustering can even be used to get a primary idea about the modelling of a particular relationship, as is done in the present case. Here, in the case of ANFIS I, the data clustering technique has been used to optimise the number of membership functions for the input and the output variables and to get an idea about the rules to be formulated. Then the membership functions as well as the rules are rationalised by following the concept of physical metallurgy of steel and the final result is found to be quite encouraging (Figure 6). The three-dimensional surface views generated from the ANFIS I after training is also in connivance with the existing understanding of the effects of these three elements with the yield strength of HSLA steel (Figure 4).

It is seen from Figures 2 and 4 that the prediction error level decreases with increase in the number of rules. But the limitations of using an ANFIS is that the number of if-then rules has to be exactly equal to the number of memberships of the output and each of these rules is assignable to only one of the memberships. It is disadvantageous for all practical purposes to divide an output range to a large number of membership functions and thus the possibility of describing the complicated relations between the inputs and the output shrinks. As a result, predictability of FIS has been found to be poor when no training is carried out (Figures 5 and 15).

As discussed earlier, the increase in the number of rules leads to an improvement in the predictability of the system. This envisages the need to gather a thorough understanding of the relations between the inputs and outputs in order to successfully design a neuro-fuzzy system. This is in total contradiction to the conventional concept of artificial neural network, where the network draws the relations between the inputs and the output without having a consideration of the physical significance of the system. Synthesisation of neural network and fuzzy system has however, acquired the ability to overcome the so-called limitation of neural network in modelling a metallurgical process with due emphasis on the existing knowledge.

On the other hand, the dependence of a neuro-fuzzy system on the if-then rules, *i.e.* the prior understanding of the relations, pose a definite limitation for modelling a neuro-fuzzy system with large number of input variables in the field of materials science. As in the case of the present exercise, the complex relationships between the composition and process variables with the mechanical properties of HSLA steel is difficult to be defined through a few if-then rules. It is necessary to formulate a large number of rules to design an effective neuro-fuzzy system. Unfortunately, this becomes a rigorous exercise and may not be considered suitable for practical use. With a view to overcome this limitation, a process of developing sub-classes has been introduced here. All the input variables are divided into four sub-classes according to their resemblance in their manner of strengthening the steel. From the available data, their contributions to the strength of HSLA steel have been separately identified. The normalised values of the contributions are used in the four separate neuro-fuzzy systems (ANFIS IIA to ANFIS IID). After training, the average prediction errors of these neuro-fuzzy systems are seen to be quite low (Figures 9,11,12 and 14). This is so possible as each of the individual systems are precisely describable with a fewer number of if-then rules.

A close look on the surface views generated from ANFIS IIA (Figure 8) after training will reveal that the effects of the elements on strength are plotted with carbon, the most common element present in the steel. The plots show that the individual strengthening effects of silicon, nickel and chromium are quite less than that of carbon (ANFIS IIA). In case of relationship between copper and molybdenum with yield strength in ANFIS IIB (Figure 10), it is found that the contribution of molybdenum towards increasing the strength of the steel is appreciably higher than that of copper. The copper addition also reaches saturation in its strengthening effect when added beyond 1.2 wt%. The surface views of niobium, titanium and boron are almost similar to that of ANFIS I (Figure 4). The surface views for the process parameters show that higher slab reheating or finish rolling temperature has a negative effect on the strength (Figure 13). Due to increase in deformation percent, the strength is seen to rise sharply, whereas for increasing the cooling rate, the strength value reaches a plateau after attainment of a rate more than that due to oil quenching.

The outputs of the four systems were further used in the integrated neuro-fuzzy system (ANFIS IIE) to obtain the final prediction about the yield strength of the steel. Here also a large improvement in the prediction error could be achieved through learning (Figures 15 and 16). ANFIS IIE is able to demonstrate the feasibility of handling a larger population of input variables in the successful design of neuro-fuzzy system by way of formulating small sub-classes with fewer numbers of variables in each sub-class.

When the subclasses form an ANFIS in accordance with Figure 7, the error value can be brought down to a significantly low level, *e.g.*, 12.5 MPa in steel of yield strength above 800 MPa. Similarly, Figure 16 shows that a very good agreement between the predicted and the target value of yield strength is achievable by this type of neuro-fuzzy system. It thus appears that the appropriate design of a neuro-fuzzy system enables to model a complicated system of non-linear input-output relationship, even if there exists no prior knowledge about the system.

6. Conclusion

(i) Neuro-fuzzy system generated through data clustering can show a good performance from the prediction point of view. It can be used to get a primary idea about the modelling of a particular relationship.

(ii) The increase in the number of rules improves the predictability of the system.

(iii) A system with a large number of input variables can be successfully designed in neuro-fuzzy system by way of formulating small sub-classes with fewer numbers of variables in each sub-class.

(iv) Appropriate design of a neuro-fuzzy system enables to model a complicated system of non-linear input output relationship, even if there exists no prior knowledge about the system.

References

[1] S Datta, J Sil and M K Banerjee *ISIJ Intl.* **39** 786 (1999)
[2] S Datta and M K Banerjee *ISIJ Intl.* **44** 846 (2004)
[3] S Datta and M K Banerjee *Scandinavian J. Metall.* **33** 310 (2004)
[4] S Datta and M K Banerjee *Mater. Proc. Tech.* (Communicated)
[5] S Datta and M K Banerjee *ISIJ Intl.* **45** 121 (2005)

[6] L A Zadeh *Information and Control* **8** 338 (1965)

[7] L A Zadeh *Computer* **1** 83 (1988)

[8] L A Zadeh *IEEE Trans. Knowledge and Data Engineering* **1** 89 (1989)

[9] B Kosko *Neural Networks and Fuzzy Systems* (New Delhi: Prentice Hall) (1994)

[10] J M Schooling, M Brown and P A S Reed *Mater. Sci Engg.* **A 260** 222 (1999)

[11] O P Femmminela, M J Starink, M Brown, I Sinclair, C J Harris and P A S Reed *ISIJ Int.* **39** 1027 (1999)

[12] S Datta and M K Banerjee *Mater Manufacturing Processes* (to be published in July 2005)*

[13] M Sugeno *Fuzzy Measures and Fuzzy Integrals: a Survey* (eds) M M Gupta, G N Saridis and B R Gaines *Fuzzy Automata and Decision Processes* (New York North-Holland) 1977

[14] S Chiu *J. Intelligent and Fuzzy Systems* **2** 319 (1994)

[15] *Boron in Steel* (eds) S K Banerji and J E Morral (Warrendale. AIME) (1979)

[16] H Tamehiro, M Murata, R Habu and M Nagumo *Trans ISIJ* **27** 120 (1987)

[17] H Tamehiro, M Murata and R Habu *Proc Int. Conf on HSLA Steels, Beijing* (ASM Int , DH, USA) 325 (1985)

[18] M Djahazi, X L He, J Jonas and W P Sun *Materials Sci. and Tech* , **8** 628 (1992)

[19] M R Krishnadev *Proc. Int. Conf on Tech and Appln. HSLA Steel* (ASM, Ohio, USA) 129 1983.

[20] M K Banerjee, D Ghosh and S Datta *Scandinavian J Met.* **29** 213 (2000)

[21] M K Banerjee, P S Banerjee and S Datta *ISIJ Int.* **41** 257 (2001)

[22] S Datta, P S Banerjee and M K Banerjee *Ironmaking and Steelmaking* **31** 312 (2004)

[23] A L Desy *Trans ISIJ* **14** 139 (1974)

[24] M Durbin and P R Krahe *Processing and Properties of Low Carbon Steel* (New York: AIMMPE)